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NETSENSE OPTIMIZING NETWORK CONFIGURATION FOR SENSING

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14. ABSTRACT
The unifying goal of this project was to characterize and optimize the interplay between network topology, communication protocols, and estimation performance. The first part of the project considered wireless sensor networks and utilized feedback from fusion sinks to optimize communication parameters for estimation objectives. The second part of the project focused on networks that employ linear network coding and produced novel methods for network tomography in this particular setting. The third part of the project, focused on learning of graphs, including but not limited to communication networks. In all cases, we designed novel network protocols and estimation methods and we showed that they advance the state-of-the art.

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EXECUTIVE SUMMARY (100-200 words):

The unifying goal of this project was to characterize and optimize the interplay between network topology, communication protocols, and estimation performance. The first part of the project considered wireless sensor networks and utilized feedback from fusion sinks to optimize communication parameters for estimation objectives. The second part of the project focused on networks that employ linear network coding and produced novel methods for network tomography in this particular setting. The third part of the project, focused on learning of graphs, including but not limited to communication networks. In all cases, we designed novel network protocols and estimation methods and we showed that they advance the state-of-the art.

List of student funded by this project:

- Pegah Sattari (fully funded)
- Furong Huang (partially funded)
- Jie Chen (fully funded)
- Feng Jiang (partially funded)

Highlights and Awards

Jie Chen and Feng Jiang received 2nd place in the Student Paper Competition at the 2012 Asilomar Conference on Signals, Systems and Computers held in November, 2012, at Pacific Grove, CA. The title of the award-winning paper was "The Gaussian CEO Problem for a Scalar Source with Memory: A Necessary Condition," and was co-authored by Prof. Lee Swindlehurst. The award included a $400 prize.

Co-PI Anandkumar received the Best Paper Award in ACM SIGMETRICS 2011 for her paper: A. Anandkumar, A. Hassidim, and J. Kelner. “Topology Discovery of Sparse Random Graphs With Few Participants”.

PART I: COMMUNICATION EFFECTS IN WIRELESS SENSOR NETWORKS

Overview: This part of the project uses feedback from network sinks (e.g., a fusion center, a communication terminal) to network sources (e.g., sensors, a multicast terminal) to allocate wireless network resources (e.g., data rates, transmission gains, UAV positions) in order to optimize performance (e.g., connectivity, estimation accuracy, throughput).

List of Publications

F. Jiang, J. Wang and A. Swindlehurst, "Interference-Aware Scheduling for Connectivity in MIMO Ad Hoc Multicast Networks," IEEE Trans. Vehicular Technology, Volume 61, No. 4, pp. 1762-1778, May, 2012.

F. Jiang and A. Swindlehurst, "Optimization of UAV Heading for the Ground-to-Air Uplink," IEEE J. of Sel. Areas in Communications, Vol. 30, No. 5, pp. 993-1005, June, 2012.

F. Jiang, J. Chen and A. Swindlehurst, "Estimation in Phase-Shift and Forward Wireless Sensor Networks," IEEE Trans. Signal Processing, Vol. 61, No. 15, pp. 3840-3851, Aug. 2013.

J. Chen, F. Jiang and A. Swindlehurst, "The Gaussian CEO Problem for Scalar Sources with Arbitrary Memory," submitted to IEEE Trans. Information Theory, June 2013.

F. Jiang, J. Chen and A. Swindlehurst, "Optimal Power Allocation for Parameter Tracking in a Distributed Amplify-and-Forward Sensor Network," submitted to IEEE Trans. Signal Processing, August 2013.

F. Jiang and A. Swindlehurst, "Dynamic UAV Relay Positioning for the Ground-to-Air Uplink," In Proc. Int'l Workshop on Wireless Networking for Unmanned Aerial Vehicles, pp. 1766-1770, Miami, FL, December, 2010.

F. Jiang, J. Chen and A. Swindlehurst, "Phase-Only Analog Encoding for a Multi-Antenna Fusion Center," in Proc. IEEE ICASSP, pp. 2645-2648, Kyoto, Japan, March, 2012.

J. Chen and A. Swindlehurst, "On the Achievable Sum Rate of Multi-terminal Source Coding for a Correlated Gaussian Vector Source," in Proc. IEEE ICASSP, pp. 2665-2668, Kyoto, Japan, March, 2012.

J. Chen, F. Jiang and A. Swindlehurst, "The Gaussian CEO Problem for a Scalar Source with Memory: A Necessary Condition," In Proc. 46th Asilomar Conference on Signals, Systems, and Computers, pp. 1219-1223, Pacific Grove, CA, November, 2012.

F. Jiang, J. Chen and A. Swindlehurst, "Parameter Tracking via Optimal Distributed Beamforming in an Analog Sensor Network," In Proc. 46th Asilomar Conference on Signals, Systems, and Computers, pp. 1397-1401, Pacific Grove, CA, November, 2012.

F. Jiang, J. Chen and A. Swindlehurst, "Linearly Reconfigurable Kalman Filtering for a Vector Process," in Proc. IEEE ICASSP, Vancouver, BC, Canada, May, 2013.

Summary of Technical Results

Estimation in Gaussian Networks and Multiterminal Source Coding: Wireless sensor networks (WSNs) are often used for distributed sensing, in which geographically distributed sensors make measurements or local estimates and forward them to a fusion center (FC), which conducts further processing to extract useful information from the data. In practice, the local measurements are typically quantized prior to transmission, and there is clearly a trade-off between the level of quantization (or equivalently the sensors' transmission rates) and the final estimation accuracy. With knowledge of the required accuracy and the statistical characteristics of the source and noise, the fusion center can optimally determine the sensors' individual transmission rates and feed this information back to the sensors in order to efficiently use the available computing and communication resources. A block diagram of the distributed estimation/communication system is depicted in Figure 1.

This type of system is equivalent to indirect multiterminal source coding, first studied in [1] and referred to as the central estimation officer (CEO) problem. In contrast to the direct multiterminal source coding problem [2], where sensors separately measure different but correlated sources and the fusion center attempts to rebuild every source as accurately as possible subject to a sum-rate constraint, each of the sensors in the CEO problem receives a noisy observation of the same source, which is later reconstructed at the fusion center. There has been a considerable body of work published on the Gaussian CEO problem, including establishment of rate regions for memoryless sources, rate-distortion trade-offs for different types of source-to-destination networks, and the development of specific coding schemes to approach the derived performance bounds [3-19].

Except for a brief discussion in [20], all previous studies have assume the sample sequence generated by the source is memoryless. In our work, we have studied the achievable sum-rate problem for a Gaussian scalar source with *arbitrary* memory. We have formulated the sum-rate calculation as a variational calculus problem with a distortion constraint, and we have shown how to find a necessary condition which the solution to the problem must satisfy. Furthermore, we can provide a sufficient condition for determining if the necessary solution achieves the minimal sum-rate performance. We demonstrate how to compute the rate-distortion curve, and we have shown that our solution is compatible with previous findings in rate-distortion theory.

For the special case of a system with two sensor nodes, we have derived an analytic expression for the solution to the sum-rate problem.

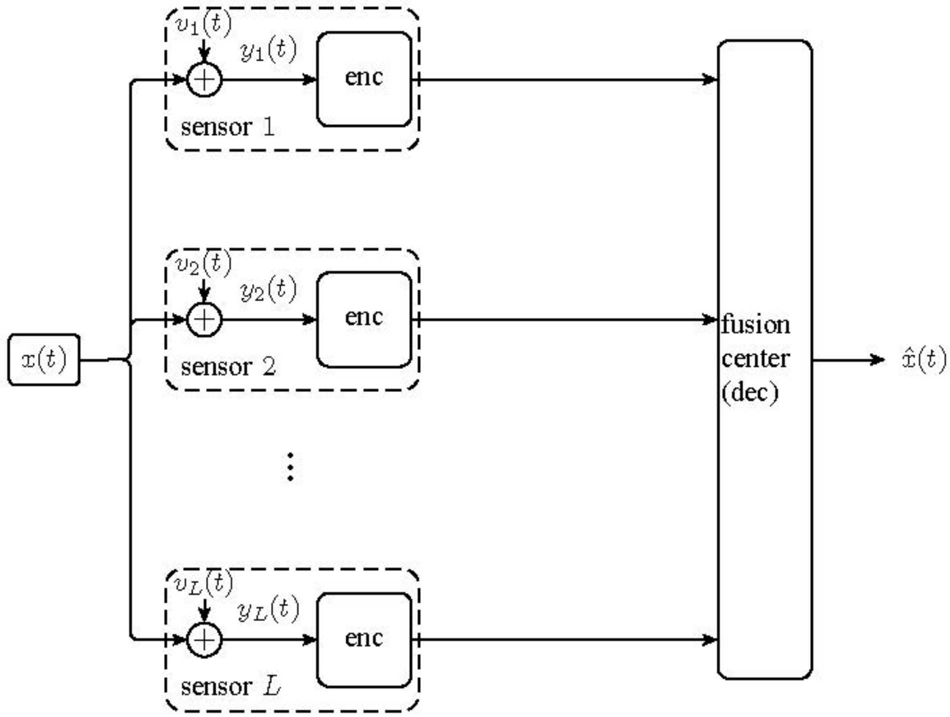

Figure 1 -- Indirect multiterminal source coding, or the "CEO Problem."

Estimation in Analog Sensor Networks (Static Parameter): Recently, considerable research has focused on the fusion of *analog* rather than encoded digital data in distributed sensor networks to improve estimation performance. The advantages of analog WSNs have been established in [21-23], where it was shown that when using distortion between the source and recovered signal as the performance metric, digital transmission (separate source and channel coding) achieves an exponentially worse performance than analog signaling.

A general analog WSN scenario is investigated in [24], involving vector observations of a vector-valued random process at the sensors, and linearly precoded vector transmissions from the sensors to a multi-antenna FC. Optimal solutions for the precoders that minimize the mean-squared error (MSE) at the FC are derived for a coherent MAC under power and bandwidth constraints. In [25], single-antenna sensors amplify and forward their observations to a multi-antenna FC, but it is shown that for Rayleigh fading channels, the improvement in estimate variance is upper bounded by only a factor of two compared to the case of a single-antenna FC. Subsequent results by the same authors in [26,27], have demonstrated that when the channel undergoes (zero-mean) Rayleigh fading, there is a limit to the improvement in detection performance for a multi-antenna FC as well, but when the channel is Rician, performance improves monotonically with respect to number of antennas.

Some prior research in radar and communications has focused on scenarios where the beamformer weights implement only a phase shift rather than both a gain and a phase. The advantage of using phase shifting only is that it simplifies the implementation and is easily performed with analog hardware. Phase-shift-only beamformers have most often been applied to receivers that null spatial interference [28,29], but it has also been considered on the transmit side for MISO wireless communications systems [30]. For the distributed WSN estimation problem, phase-only sensor transmissions have been proposed in [31], where the phase is a scaled version of the observation itself. Phase-only transmissions were also considered in the context of distributed detection in [26].

For this project, we have studied a distributed WSN with single-antenna sensors that observe an unknown deterministic parameter corrupted by noise. The low-complexity sensors apply a phase shift (rather than both a gain and phase) to their observation and then simultaneously transmit the result to a multi-antenna FC over a coherent MAC. The FC determines the optimal value of the phase for each sensor in order to minimize the ML estimation error, and then feeds this information back to the sensors so that they can apply the appropriate phase shift. The estimation performance of the phase-optimized sensor network has been shown to be considerably improved compared with the non-optimized case, and close to that achieved by sensors that can adjust both the transmit gain and phase. We analyzed the asymptotic behavior of the algorithm for a large number of sensors and a large number of antennas at the FC. In addition, we analyzed the impact of phase errors at the sensors due, for example, to errors in the feedback channel, a time-varying main channel or phase-shifter drift. We also considered a sensor selection problem, and analyzed its asymptotic behavior as well. Some particular findings of our research are highlighted below.

- We have derived two algorithms for determining the phase factors used at each sensor. In the first, we use semi-definite relaxation to convert the original problem to a semidefinite programming (SDP) problem that can be efficiently solved by interior-point methods. For the second algorithm, we apply the analytic constant modulus algorithm (ACMA) [32], which provides a considerably simpler closed-form solution. Despite the reduction in complexity, the performance of ACMA is shown via simulation to be only slightly worse than the SDP solution, and close to the theoretical lower bound on the estimate variance. This is especially encouraging for networks with a large number of sensors N, since the SDP complexity is on the order of $N^{3.5}$, while that for ACMA is only on the order of N^2.

- We have separately derived performance scaling laws with respect to the number of antennas and the number of sensors assuming non-fading channels that take path loss into account. For both cases, we derived conditions that determine whether or not the presence of multiple antennas at the FC provides a significant benefit to the estimation performance. Prior work in [25-27] has focused on either AWGN channels with identical channel gains, or on fading channels where the channel gains are identically distributed, corresponding to the case where the distances from the sensors to the FC are roughly the same. References [25-27] also assume a special case where the noise at each of the sensors has the same variance, although [27] examines how certain upper bounds on performance change when the sensor noise is arbitrarily correlated.

- Using our model for the non-fading case, we are able to elucidate detailed conditions under which the asymptotic estimation performance will improve with the addition of more antennas *M* at the FC. While [25,26] showed that performance always improves with increasing *M* for AWGN channels with identical gains and identically distributed sensor noise, we derive more detailed conditions that take into account the possibility of non-uniform distances between the sensors and FC and non-uniform noise at the sensors.

Estimation in Analog Sensor Networks (Dynamic Parameter): As described above, most prior work on estimation in distributed amplify-and-forward sensor networks has focused on the situation where the parameter(s) of interest are time-invariant, and either deterministic or i.i.d. Gaussian. An exception is the recent work by Leong et al, who model the (scalar) parameter of interest using a dynamic Gauss-Markov process and assume the FC employs a Kalman filter to track the parameter [33,34]. In [33], both the orthogonal and coherent MAC were considered and two kinds of optimization problems were formulated: MSE minimization under a global sum transmit power constraint, and sum power minimization problem under an MSE constraint. An asymptotic expression for the MSE outage probability was also derived assuming a large number of sensor nodes. The problem of minimizing the MSE outage probability for the orthogonal MAC with a sum power constraint was studied separately in [34].

Our work has focused on the coherent MAC case assuming a dynamic parameter that is tracked via a Kalman filter at the FC. As detailed in the list of contributions below, we have extended the work of [33] for the case of a global sum power constraint, and we go beyond [33] to study problems where either the power3of the individual sensors is constrained, or the goal is to minimize the peak power consumption3of individual sensors:

- We derived a closed-form expression for the optimal complex transmission gains that minimize the MSE under a constraint on the sum power of all sensor transmissions. While this problem was also solved in [33] using the KKT conditions derived in [24], our approach results in a simpler and more direct solution. We also examine the asymptotic form of the solution for high total transmit power or high noise power at the FC.

- We derived a closed-form expression for the optimal complex transmission gain that minimizes the sum power under a constraint on the MSE. In this case, the expression depends on the eigenvector of a particular matrix. Again, while this problem was also addressed in [33], the numerical solution therein is less direct than the one we obtain. In addition, we found an asymptotic expression for the sum transmit power for a large number of sensors.

- We have shown how to find the optimal transmission gains that minimize the MSE under individual sensor power constraints by relaxing the problem to an SDP, and then proving that the optimal solution can be constructed from the SDP solution.

- We have shown how to find the optimal transmission gains that minimize the maximum individual power over all of the sensors under a constraint on the maximum MSE. Again, we solved the problem using SDP, and then proved that the optimal solution can be constructed from the SDP solution.

- For the special case where the sensor nodes use equal power transmission, we derived an exact expression for the MSE outage probability.

UAV Positioning for Communications: In military or disaster response (e.g., fire fighting) scenarios, users on the ground require reliable communications with each other and their command center. Such scenarios often occur in environments without a fixed communications infrastructure (e.g., a centralized basestation as in cellular networks), and thus the network must operate in a peer-to-peer or ad hoc manner. The users and the command center may be separated by distances greater than the range of their communication devices, or the signals may be shadowed due to mountainous terrain or dense surroundings (forests, buildings, etc.). Furthermore, since the users are mobile, the communications environment is constantly changing and thus connectivity is often only sporadic. Unmanned aerial vehicles (UAVs) acting as airborne relays (essentially "flying basestations") provide an attractive solution to problems encountered in such scenarios since their altitude allows them to get above the ground-based shadowing and obtain line-of-sight (LOS) or near LOS communication channels over a large area. Also and perhaps most importantly, the inherent mobility of UAVs allows their position to be adjusted in order to best accommodate the evolving network topology. We have considered such an application under this project, assuming a system with a multi-antenna UAV flying over a collection of single-antenna mobile ground nodes. The UAV acts as a relay, collecting the messages from the co-channel users on the ground in order to forward them to other ground-based users or some remote base station. The goal is to show how to control the motion of the UAV so as to optimize the uplink communications performance.

In particular, in our work we have investigated the problem of positioning a multiple antenna UAV for enhanced uplink communications from multiple ground-based users. We studied the optimal UAV trajectory for a case involving two static users, and derived an approximate method for finding this trajectory that only requires a simple line search. For the case of a network of mobile ground users, we developed an adaptive heading algorithm that uses predictions of the user terminal positions and beamforming at the UAV to maximize SINR at each time step. Two kinds of optimization problems were considered, one that maximizes an approximation to the average uplink sum rate and one that guarantees fairness among the users using the proportional fair method. Our simulation studies indicate the effectiveness of the algorithms in automatically generating a suitable UAV heading for the uplink network, and demonstrate the benefit of using space-division multiple access (SDMA) over time-division multiple access (TDMA) in achieving the best throughput performance. We also derived approximate solutions to the UAV heading problem for low- and high SNR scenarios; the approximations allow for a closed-form solution instead of a line search, but still provide near-optimal performance in their respective domains.

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PART II: NETWORK CODING and INFERENCE

Overview: When a communication network employs linear network coding at intermediate nodes, it essentially acts as a linear system whose transfer function depends primarily on the network topology and secondarily on the network coding coefficients. In this part of the project, we exploited this intimate relation between network coding and network topology for inference problems. In particular, we revisited network tomography and we designed novel active probing and estimation techniques.

List of publications:

[THESIS] P. Sattari, "Network Coding for Network Tomography," *Ph.D. Thesis*, University of California, Irvine, May 2012. (The main contributions [NC1, NC2, NC5, NC6, NC8] are summarized below.)

[NC1] P. Sattari, A. Markopoulou, C. Fragouli, M. Gjoka, "A Network Coding Approach to Loss Tomography," *in IEEE Transactions on Information Theory*, Vol. 59, Issue 3, pp. 1532 - 1562, March 2013

[NC2] P. Sattari, C. Fragouli, A. Markopoulou, "Active Topology Inference using Network Coding," *in the Elsevier Physical Communication, Special Issue on Network Coding and its Applications to Wireless Communications*, Vol. 6, pp. 142 - 163, March 2013.

[NC3] Chun Meng, Hulya Seferoglu, A. Markopoulou, Kenneth W. Shum, Chung Chan, MPC: Multicast Packing for Coding across Multiple Unicasts", *in Proc. of NetCod 2013*, June 2013. Technical report.

[NC4] A. Le, A. Tehrani, A. Dimakis, and A. Markopoulou, "Instantly Decodable Network Codes for Real-Time Applications", *in Proc. of NetCod 2013*, June 2013

[NC5] P. Sattari, Maciej Kurant, Animashree Anandkumar, A. Markopoulou, Michael Rabbat, Active Learning of Multiple Source Multiple Destination Topologies, *in Proc. of CISS 2013*, March 2013.

[NC6] P. Sattari, A. Markopoulou, C. Fragouli, "Maximum Likelihood Estimation for Multiple-Source Loss Tomography with Network Coding," *in Proc. of NetCod 2011*, pp. 5-11, Beijing, China, July 25-27, 2011.

[NC7] A.Le, A. Markopoulou, "TESLA-Based Defense Against Pollution Attacks in P2P Systems with Network Coding," *in Proc. of NetCod 2011*, Beijing, China, July 2011.

[NC8] P. Sattari, A. Markopoulou, "Algebraic Traceback Meets Network Coding," *in Proc. of NetCod 2011 (Poster Session)*, pp. 253-259, Beijing, China, July 2011.

[OSN1] M.Gjoka, M.Kurant, A.Markopoulou, "2.5K-Graphs: from Sampling to Generation", *in Proc. of IEEE INFOCOM 2013*, Turin, Italy, March 2013.

[OSN2] F. Malandrino, M.Kurant, A. Markopoulou, C.Westphal, U.Kozat, "Proactive Seeding for Information Cascades in Cellular Networks", *in Proc. of IEEE INFOCOM 2012, Orlando, FL, March 2012.*

Summary of Technical Results

Network tomography aims at inferring internal network characteristics, such as topology and/or link-level characteristics (such as loss rate or delay), based on measurements at the edge of the network. There is a significant body of prior work dedicated to this problem using multicast and/or unicast end-to-end probes. Independently, recent advances in network coding have shown that there are several advantages from allowing intermediate nodes to process and combine, in addition to just forward, packets.

In this part of the project, we revisit the problem of network tomography (which allows us to send probes between sources and receivers at the edge of the network), with network coding (which allows intermediate nodes to perform simple coding operations on incoming packets). We showed that network coding offers several benefits in terms of complexity, accuracy, and bandwidth savings. Our key intuition is that network coding at intermediate nodes introduces topology-dependent correlation in the content of coded packets, which can then be exploited for inferring the coding points. We made the following contributions in this area:

- First, we revisited multiple-source loss tomography in tree topologies with multicast and network coding capabilities, and we provide, for the first time, a low-complexity Maximum Likelihood Estimator (MLE) for the link loss rates [NC1, NC6]. In addition to the MLE, we also applied and evaluated message-passing algorithms for link loss estimation, both in trees and in general topologies.

- Second, we studied the topology inference problem in multiple-source multiple-receiver (M-by-N) networks [NC2]. We built on prior work by one of our collaborators (M. Rabbat), which infers a general M-by-N topology by first inferring several 2-by-2 subnetwork components, and then merging them to obtain the M-by-N topology. We showed that, with simple network coding operations at intermediate nodes, it is possible to perfectly identify every 2-by-2 component, which is not possible using only multicast or unicast probes. Furthermore, we proposed a new algorithm for merging all 2-by-2 components to obtain the M-by-N topology. We cast the problem as multiple hypotheses testing (in particular, generalized binary search) [NC5] and we designed and analyzed a greedy algorithm that adaptively selects which 2-by-2 components to measure so as to minimize the number of measurements needed to infer the M-by-N topology.

- Third, we revisited the traceback problem, which arises in the context of denial-of-service attacks, where multiple attack sources flood a victim destination by sending a large number of packts. The goal of traceback is to identify the paths traversed by these malicious packets all the way back to the attack sources, by allowing intermediate nodes to mark a dedicated held on headers of packets passing through them with the node id. We incorporated, for the first time, network coding in two different types of traceback schemes: probabilistic packet marking schemes and algebraic traceback [NC8]. In probabilistic packet marking, routers probabilistically mark packets with (a function of) their router id. We demonstrated the benefit of network coding, by essentially reducing the traceback problem to a coupon collector's problem. In contrast, algebraic traceback encodes the ids of routers on a single path as coefficients in a polynomial of a single variable. We extended that idea to encode multiple paths into a multivariate polynomial and we establish an interesting mapping between multi-path algebraic traceback and a particular network coding problem.

The aforementioned study of inference in network coded networks, led to a deeper understanding of the effect of topology in other network coding problems, such as security and pollution attacks [NC7], instantly decodable network coding [NC4], and constructive inter-session network coding schemes [NC3]. Furthermore, it provided valuable insight into a different thread of research in our group, which investigated the topology of online social networks with target applications simulation [OSN1] and information diffusion [OSN2].

PART III: LEARNING GRAPH-BASED MODELS

<u>Overview:</u> This part of the project deals with graphs beyond communications networks and seeks to learn network structure using adaptive techniques. Today we are facing a ``data deluge'' in almost every domain. The collected data in many domains are noisy, subsampled, with typically a large number of variables or ``unknowns'' compared to the number of observations or the ``knowns''. Such high-dimensionality entails practical principled approaches for learning from ill-posed and ill-behaved data. As part of this project, we tackled high dimensional learning by exploiting inherent data structure, either in the form of structural relationships among the variables, represented as graphs or as parametric forms, represented as tensor decompositions. Below we summarize the publications and some key results in learning of graph-based models.

<u>List of Publications:</u>

A. Anandkumar, A. Hassidim, and J. Kelner. Topology Discovery of Sparse Random Graphs With Few Participants. In Proc. of ACM SIGMETRICS, June 2011. Winner of Best Paper Award.

A. Anandkumar, K. Chaudhuri, D. Hsu, S.M. Kakade, L. Song, and T. Zhang. Spectral Methods for Learning Multivariate Latent Tree Structure. In Proc. of Neural Information Processing (NIPS), Dec.2011.

A. Anandkumar, V. Y. F. Tan, and A. S. Willsky. High-Dimensional Graphical Model Selection: Tractable Graph Families and Necessary Conditions. In *Proc. of Neural Information Processing (NIPS)*, Dec. 2011.

A. Anandkumar, V.Y.F Tan, F. Huang, and A.S. Willsky. "High-Dimensional Structure Learning of Ising Models: Local Separation Criterion". Annals of Statistics, Volume 40, Number 3 (2012), 1346-1375.

Anandkumar, V.Y.F Tan, F. Huang, and A.S. Willsky. "High-Dimensional Gaussian Graphical Model Selection: Walk-Summability and Local Separation Criterion". A. J. Machine Learning Research, 13:2293–2337, Aug. 2012

A. Anandkumar, D. Hsu, and S.M. Kakade. A Method of Moments for Mixture Models and Hidden Markov Models. In Proc. of Conf. on Learning Theory, June 2012.

M. Janzamin and A. Anandkumar. High-Dimensional Covariance Decomposition into Sparse Markov and Independence Domains. In Proc. of International Conf. on Machine Learning, June 2012.

A. Anandkumar, D. Hsu, F. Huang, and S.M. Kakade. Learning Mixtures of Tree Graphical Models. In Proc. of Neural Information Processing (NIPS), Dec. 2012.

A. Anandkumar and R. Valluvan. Learning Loopy Graphical Models with Latent Variables: Efficient Methods and Guarantees. In Proc. of Neural Information Processing (NIPS), Dec. 2012.

A. Anandkumar, D. P. Foster, D. Hsu, S. M. Kakade, and Y. K. Liu. A Spectral Algorithm for Latent Dirichlet Allocation. In Proc. of Neural Information Processing (NIPS), Dec. 2012.

A. Anandkumar, D. Hsu, A. Javanmard, and S. M. Kakade. Learning Bayesian Networks with Latent Variables. In *Proc. of Intl. Conf. on Machine Learning*, June 2013.

Anandkumar, R. Ge, D. Hsu, and S. M. Kakade. A Tensor Spectral Approach to Learning Mixed Membership Community Models. In *Conference on Learning Theory (COLT)*, June 2013.

R. Valluvan, Z. W. Almquist, C. T. Butts, and A. Anandkumar. Semi-parametric vertex set prediction for dynamic networks using latent tree models. In Intl. Conf. for Social Network Analysis (Sunbelt 2012), Redondo Beach, CA, March 2012.

Summary of Technical Results:

Probabilistic Graphical Models: One graphical framework for rep-resenting high-dimensional data is that of probabilistic graphical models, also known as Markov random fields or Markov networks. A Markov network represents complex relationships between data at different nodes in the form of a graph, known as the dependency graph. Mathematically, any two sets of nodes A and B are conditionally independent, conditioned on the separator set S: XA ⊥ XB|XS. Hence, the data at each node is influenced by its neighbors in the dependency graph. A Markov representation is succinct with a much smaller number of parameters than the number of data dimensions (variables), and it explicitly encodes the relationships between the variables.

Formulation of Learning from Data: Given n i.i.d. data samples xn := $[x(1), x(2), . . . , x(n)]^T$ from a graphical model P with Markov graph G, the goal is to estimate the underlying graph. We developed methods and provided consistency guarantees for graph estimation in the high dimensional regime.

Structure Learning with Hidden Variables: Developing tractable methods to discover hidden nodes and the overall graph structure(s) (and parameters) was an important goal of this project. Co-PI Anandkumar has developed efficient methods for learning latent variable models in a variety of settings. This includes the development of novel methods for learning hidden tree models. The developed algorithms have low sample complexity and are much faster and more robust than the state of art. The algorithm, at a high level, maintains a tree model in each iteration and adds hidden variables by conducting local tests. This property is unique to our approach and makes it amenable for applying it to real data since we can tradeoff model complexity and data fitting in a principled and an efficient manner. We extended these methods for learning latent loopy models with long cycles [NIPS'2012], and demonstrated effectiveness in financial and topic modeling.

Bayesian Networks with Latent Variables: In addition to incorporating latent variables, it is important to model the complex dependencies among the variables. In [ICML'13], we provided novel methods for learning directed acyclic graphs (DAG) with hidden variables. The method is based on the intuition that learning is tractable when there is sufficient expansion in the DAG from hidden to observed variables (e.g. when it is latent tree or has small number of collidiers, i.e., nodes with multiple parents). This work combines sparse dictionary learning with method of moments in a novel manner and is the first work to provide guaranteed learning for latent Bayesian networks. This has implications in many practical settings, e.g. for learning correlated topic models.

Modeling Using Multiple Graphs: Modeling high-dimensional data involves a delicate trade- off between faithful representation and parsimony. Models that are sparse in some domain achieve a parsimonious representation but may poorly fit the given data. We has developed frameworks for relaxing the sparsity constraints without sacrificing on parsimony in high dimensions. One framework involves incorporating hidden factorswhich can change the structural (and parametric) relationships among the observed variables [NIPS'13], thereby resulting in a mixture of probabilistic graphical models. We developed methods with guaranteed recovery of mixture components that are also efficient for practical implementation. We also considered another approach for modeling with multiple graphs. In [ICML'12], the observed data is fitted to a combination of a sparse graphical model and a sparse independence model, thereby incorporating different kinds of statistical relationships among the variables. We developed novel decomposition methods based on convex relaxation with guaranteed recovery in both the domains.

Finally, we applied the above developed algorithms to a number of practical problems, including financial and document modeling, object recognition in computer vision, to track the evolution of dynamic social networks [Sunbelt 2012] and to model gene associations. We have shown a huge improvement over previous ones in all these instances.